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Against all odds: multicriteria decision making with hazard prediction maps depicting uncertainty

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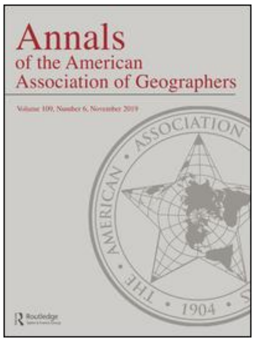

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Against All Odds: Multicriteria Decision Making with Hazard Prediction Maps Depicting Uncertainty

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We report on a multicriteria decision-making study where participants were asked to purchase a house shown on maps that include hazard prediction information. We find that participants decided to buy different houses, depending on whether uncertainty is shown on the map display and on the type of uncertainty visualization (i.e., varying color value, focus, or texture). We also find that participants' individual differences with respect to their assessed risk-taking behavior influences their spatial decision making with maps. Risk-takers seem to underestimate the dangers of natural hazards when prediction uncertainties are depicted. We are thus able to shed additional light on how people use visualized uncertainty information to make complex map-based decisions. We can demonstrate that not only are design characteristics relevant for map-based reasoning and decision-making outcomes but so are the decision makers' individual background and the map-based decision-making context. *Key Words: experiment, risk maps, risk perception, uncertainty, visualization.*

我们报告一个多准则决策研究, 其中参与者被要求购买包含灾害预测信息的地图上显示的房子。我们发现, 参与者根据不确定性是否展现在地图上以及不确定性可视化的种类（例如不同的颜色价值、焦点或纹理）, 购买不同的房子。我们同时发现, 与参与者评估的风险承受行为相关之个人差异, 影响了他们在地图上的空间决策。当预测的不确定被描述时, 承担风险者似乎会低估自然灾害的危险。我们因而能够对于人们如何运用可视化的不确定性信息来进行以地图为基础的复杂决策, 提出近一步的洞见。我们能够证明, 不仅是设计特徵与根据地图的论据及决策结果有关, 决策者的个人背景和以地图为基础的决策脉络亦有关。*关键词: 实验, 风险地图, 风险认知, 不确定性, 可视化。*

Informamos acerca de un estudio de criterios múltiples sobre toma de decisiones en donde a los participantes se les pidió comprar una casa mostrada en mapas que incluían información sobre predicción de riesgos. Encontramos que los participantes decidieron comprar diferentes casas, dependiendo de si la incertidumbre es mostrada en el despliegue cartográfico, y del tipo de visualización de la incertidumbre (o sea, valor variable del color, foco, o textura). Descubrimos también que las diferencias individuales de los participantes con respecto de su evaluación de la conducta de asumir riesgos influyen en su toma de decisiones espaciales con mapas. Aquellos que toman riesgos parecen subestimar los peligros de las amenazas naturales cuando la predicción de las incertidumbres es mostrada. De ese modo podemos dar mayor ilustración sobre cómo la gente usa la información visualizada sobre incertidumbre para tomar decisiones complejas con base en mapas. Podemos demostrar que no solo son relevantes las características del diseño para razonamiento basado en mapas y para los resultados en la toma de decisiones, sino también lo son los antecedentes individuales de quienes toman las decisiones y el contexto de la toma de decisiones con base en mapas. *Palabras clave: experimento, incertidumbre, mapas de riesgos, percepción del riesgo, visualización.*

The study of how humans deal with uncertain information has been a long-standing research agenda in many areas of science (Tversky and Kahneman 1974), including geography and geographic information science. Although a wealth of design strategies have been proposed by an interdisciplinary scientific community to visually communicate data uncertainty for spatiotemporal decision-making contexts (Pang 2001; MacEachren et al. 2012; Liu et al. 2017; Correll, Moritz, and Heer

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2018; Liu et al. 2019), few researchers have looked at specifically how users make visuospatial decisions with uncertain information and how the visualization of uncertainty in graphic displays might influence the spatiotemporal decision-making process. How uncertainty depictions influence open-ended, complex, multicriteria map-based decision outcomes, such as for potentially dilemmatic problems for which uncertainty truly matters (e.g., making decisions in the presence of hazards and risks), is underresearched to date (Padilla, Ruginski, and Creem-Regehr 2017). We aim to narrow these research gaps and wish to shed additional light on how people use visualized uncertainty information to make complex map-based decisions. For example, buying a house is already a complex decision-making process. What factors influence people's multicriteria decision-making process when asked to purchase a house shown on maps that include hazard prediction information? Our leading research questions center on how map design characteristics influence map-based reasoning and decision-making outcomes under uncertainty and what role decision makers' individual backgrounds play in this specific map-based decision-making context.

Background

Decision Making in an Uncertain World

Geographic information presented on maps has been used for a long time to help humans make important and relevant space–time decisions. Hope and Hunter (2007a, 2007b) suggested that at least 80 percent of the public sector (e.g., resource management, planning, emergency response and mitigation, etc.) uses geographic information to make societally relevant decisions. More recently, the digital information society increasingly peruses geographic information for decisions, supported by (big) data mining, such as in predictive spatiotemporal modeling and decision support scenarios in various application areas including infrastructure management in smart cities, security applications, or natural hazards (Riveiro et al. 2014; Padilla 2017; Batty 2018). These scenarios are inherently based on uncertainty in data, models, and prediction outcomes (Kahneman 2011). Government authorities depend heavily on geographic information for decision making under uncertainty, but spatial data sets have also become increasingly important for decision making in the private sector; for example, in real estate applications, advertising, election campaigning, business analytics and geo-marketing, hazard and risk assessments in the insurance industry, and transport logistics, just to mention a few (Hope and Hunter 2007a, 2007b). Beyond the application areas just mentioned—where geographic information is used for modeling, prediction, human inference and decision making, and action support—uncertainty is inserted into the analytics process and the behavioral outcomes (Liu et al. 2017; Liu et al. 2019). This can be due to measurement inaccuracies in the source data, uncertainties introduced in spatial data pre- and postprocessing, misspecifications of model variables or data parameters, propagated uncertainties in simulation runs, or predictive models of space–time phenomena and processes (Zhang and Goodchild 2002). Simply put, all spatial data on which our space–time decisions are based are indeed subject to uncertainties (Duckham et al. 2001).

Uncertainty itself is an elusive and abstract concept. There is no generally accepted definition of *uncertainty* (Griethe, Schumann, and SimVis 2006; Smith et al. 2013), which makes it difficult to deal with uncertainty, especially in an interdisciplinary context. Even though it is difficult to deal with uncertainty, this inherent property of the data cannot simply be ignored (Zhang and Goodchild 2002). Hunter and Goodchild (1993) defined uncertainty as the unknown difference between reality and measured data. A decision based on data without considering the associated uncertainty is not an informed decision. In the worst case, uninformed decisions could lead to loss of life (e.g., due to natural hazards), or poorly informed decisions could lead to significant economic losses (e.g., because of unpredictable stock market responses or infrastructure failures; Liu et al. 2017; Padilla 2017; Liu et al. 2019).

The decision sciences have for a long time studied how humans make decisions, including under uncertainty (Kahneman 2011). Everyday decisions are very often not made rationally or consciously but are rather based on so-called heuristics (or rules-of-thumb), especially when decisions are complex or have to be made in stressful situations or under time pressure (Kahneman 2011). Heuristics are informal decision rules that simplify the process of evaluating different results under uncertainty (Simon 1956). Tversky and Kahneman (1974) presented a series of heuristic approaches that are applied to decision making under uncertainty. They found that although heuristics can be useful in some cases, and especially in time-critical situations, they can also lead to systematic errors or cognitive biases. The role of heuristics in map-based decision making under uncertainty still remains an elusive and open research question (Keuper 2004).

Map-Based Decision Making with Uncertainty

Because geographic information is typically communicated by means of map displays for space–time decision making, data uncertainty in the map can also be visualized (Smith Mason, Retchless, and Klippel 2017). Although there has been a long tradition of visualizing uncertainty in maps (Pang 2001; MacEachren et al. 2005; Kinkeldey, MacEachren, and Schiewe 2014), we only recently gained empirical evidence into what kinds of uncertainty visualizations work and how they work (Kinkeldey, Schiewe, et al. 2015). Various studies have shown that the visualization of uncertainty does indeed influence decisions (Kinkeldey, Schiewe, et al. 2015). Most of these studies, however, have focused on the outcomes of decision making and not on the process. They typically investigated how accurately and quickly a decision was made or how confident the decision makers were with their made decisions. For example, Leitner and Buttenfield (2000) found that the visualization of data uncertainty on maps increases the accuracy of map-based decisions. In this case, the visualization of data uncertainty has a positive effect on decision making. On the other hand, Hope and Hunter (2007a) contended that decision makers also make irrational and unreasonable decisions with displays that include the visualization of uncertainty. Hence, it is still an open research question whether, how, and why the inclusion of uncertainty influences decision making. Only a few empirical studies have investigated whether the visualization of uncertainty influences decision-making performance more generally, irrespective of decision accuracy (Kinkeldey, MacEachren, et al. 2015). Various researchers have found that, dependent on the visualization of uncertainty, decision outcomes (beyond accuracy) can indeed be different (Deitrick and Edsall 2006; Pyysalo and Oksanen 2014; Riveiro et al. 2014). Kinkeldey, MacEachren, et al. (2015) reported a widely held belief that the visualization of uncertainty instills decision makers with greater confidence in their decisions. Fisher, Popov, and Drucker (2012) could observe this effect for nonspatial data. Studies with geographic data, however, have not yet directly shown this positive effect. Considering response confidence as one aspect of decision-making performance, or decision outcome, Leitner and Buttenfield (2000), Deitrick and Edsall (2006), and Riveiro et al. (2014) could not find significant differences between decisions made with or without the visualization of uncertainty. When the appropriate visualization of uncertainty is applied, Kinkeldey, MacEachren, et al. (2015) contended that response confidence can only increase given that decision makers understand the uncertainty visualization principle (MacEachren et al. 2012). Empirical uncertainty research is still inconclusive regarding whether prior training, experience, or domain expertise might influence map-based decision making with or without the visualization of uncertainty and how it does (Smith Mason, Retchless, and Klippel 2017). Whereas Evans (1997) and Aerts, Clarke, and Keuper (2003) did not find any difference in decision-making outcomes due to expertise, St. John et al. (2000), Kobus, Proctor, and Holste (2001), Hope and Hunter (2007a), and Roth (2009) did find that the experience of a decision maker can influence decisions with the visualization of uncertainty. Leitner and Buttenfield (2000) and Riveiro et al. (2014) also found that the visualization of uncertainty has no influence on the time taken to make a map-based decision. How decision makers arrive at their decision with and without the visualization of uncertainty, however, has, to date, been far less studied empirically, especially in a geographical context (e.g., Keuper 2004; McKenzie et al. 2016; Ruginski et al. 2016). Except for Keuper's (2004) seminal but unpublished study, where participants were tested in an open-ended multicriteria decision-making context (i.e., apartment selection task), experimental tasks were not complex. Kinkeldey, MacEachren, et al. (2015) and McKenzie et al. (2016) identified this as a gap in the literature.

Summarizing prior empirical uncertainty decision-making research, the visualization of uncertainty can influence decision outcomes (e.g., Deitrick and Edsall 2006; Pyysalo and Oksanen 2014; Riveiro et al. 2014; Liu et al. 2017, 2019; Padilla, Ruginski, and Creem-Regehr 2017). The visualization of uncertainty can also have a direct influence on the accuracy of decisions (see, e.g., Andre and Cutler 1998; Leitner and

Buttenfield 2000; Hope and Hunter 2007b). Furthermore, uncertainty can be visualized in different ways, which, in turn, can also influence decision outcomes (see, e.g., Hope and Hunter 2007a; Cheong et al. 2016; Smith Mason, Retchless, and Klippel 2017). This raises the following empirical research questions: How does the visualization of uncertainty lead to different map-based decision outcomes? How does the process of complex decision making with the visualization of uncertainty work? What roles do decisions makers' background and training play?

An Empirical Map-Based Decision-Making Study

In our empirical study, we wish to address two research gaps. On the one hand, we wish to further advance the research frontier of geographic information visualization with uncertainty by specifically focusing on the quality (or type) of decision outcomes, specifically when nondomain experts make complex decisions with maps containing spatial uncertainty visualized in different ways. Unlike most prior empirical research, we are not only interested in how fast or how accurate map-based decision outcomes are, dependent on visualized uncertainty. Informed by Hope and Hunter's (2007a, 2007b) prior research and by others reviewed earlier (e.g., Kinkeldey, MacEachren, et al. 2015), we hypothesize that decision outcomes will be different with and without the depiction of uncertainty and decision outcomes will also depend on the manner with which the uncertainty is depicted.

The second objective of our research is to more deeply understand the decision-making process itself when nondomain experts make decisions in a use-inspired, but complex, multicriteria decision-making context. As mentioned earlier, the decision science literature suggests various types of heuristic approaches to decision making under uncertainty. We wish to further investigate what the available heuristics are that participants intuitively employ for map-based multicriteria decision making and how chosen heuristics might change, dependent on whether uncertainty is depicted or not and on how uncertainty is depicted. We pursue these questions with a controlled empirical lab study, as we detail next.

Experimental Design

We present a map-based, multicriteria decision-making experiment with nondomain experts, following a within-subject design. The depiction of uncertainty (two levels: yes–no) and the type of uncertainty depiction (three levels: color value, focus, and texture) represent the independent variables that we controlled in this experiment. Decision outcomes, response time, and participants' eye movement patterns were the dependent variables we measured in this study. We do not report on decision time and the eye movement analysis in this article, due to space constraints.

We asked participants to imagine purchasing a home, shown on sixteen map stimuli inspired by Swiss National hazard prediction maps (Swiss Federal Office for the Environment [SFOEN] 2016). When deciding to buy a home, participants must consider the characteristics of the house, such as its location, the house price, and potential risks from natural hazards. Twelve maps included the visualization of uncertainty at hazard zone boundaries, and four maps did not. Of the twelve map stimuli that did include uncertainty information, three sets of four maps used the visual variables color value, focus, or texture to visually convey uncertainty information. We chose sixteen stimuli in total so that we could keep the testing time below the one-hour mark to mitigate testing fatigue. To further control for fatigue and potential learning bias, we assigned participants randomly to three map display series. In each series, participants viewed map stimuli in one of three map display sequences that were determined with a random number generator. The random sequence ensures that even if a learning effect occurred, it would not have affected the results for individual visualizations. As we wished to assess the intuitiveness of the uncertainty depiction types and their influence on complex decision making, at no time in the experiment did we give any indication that the various map types were supposed to depict data uncertainty. The results of our user study are intended to provide further insights on the influence of the visualization of uncertainty in complex decision-making contexts. The aim was to suggest design guidelines for map-based decisions under uncertainty and, more important, to support future decision makers to make better decisions.

Methods

Participants

As already mentioned in the review of prior empirical research, domain experience and expertise—for

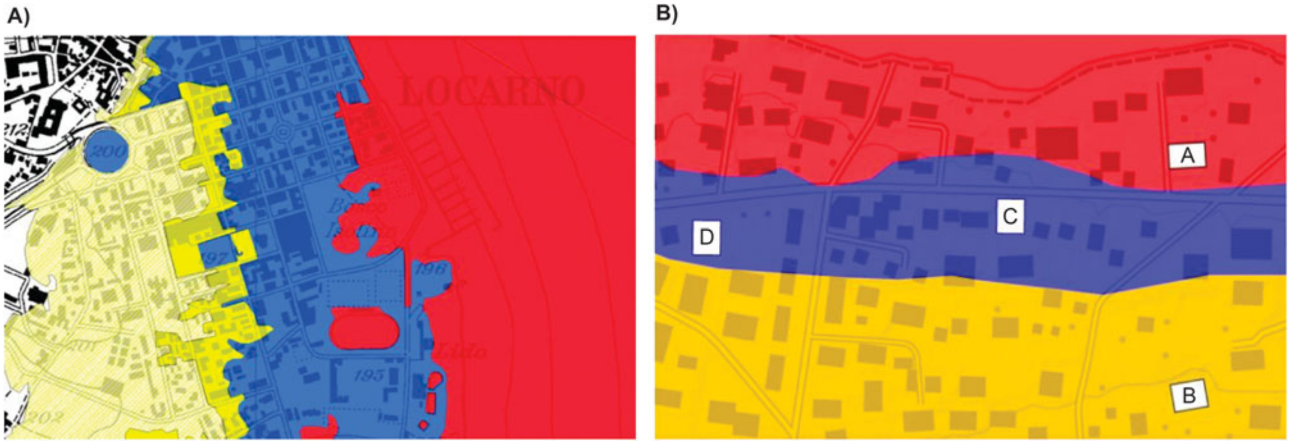

Figure 1. (A) original hazard prediction map (Swiss Federal Office for the Environment 2016); (B) developed test stimuli.

instance, in geography, cartography, geographic information systems (GIS) or with hazard and risk assessments—could have an impact on decisions to be made with hazard prediction maps showing uncertain geographic information. Because the aim of our work is not to test the influence of background knowledge and training (i.e., any differences in behavior that might emerge from differences in knowledge), we aimed for a participant group that was not only homogeneous in age, background and training, and experience but also balanced in gender. For this reason, we invited thirty-seven students from the University of Zurich (UZH) to participate in our study. These students were all within a given age range (22–32 years; $M = 24.7$ years), well acquainted with cartography and GIS, and used to looking at maps. Clearly, these participants have limited to no experience in the chosen decision-making context; that is, house selection under uncertainty with hazard prediction maps. Given that less than 30 percent of the Swiss population owns a house in Switzerland, home-buying expertise is generally rather low in any potential test population from this country. Another reason for our sample choice is that we do not focus on how well our participants can buy a home but rather what type of home they would buy and how the depiction of uncertainty might change their choice. We wished to have a population that was trained well enough to handle a map reading task to avoid potential map reading biases. Participation was solicited via e-mail, by the first author, at that time a master's student in the UZH Geography Department.

Setup and Materials

The entire study took place in the Eye Movement Lab (EML) of the UZH Geography Department. The EML lab is a windowless room. Hence, all participants had the same lighting conditions, regardless of the time of day at which the study was carried out. The EML is equipped with a Tobii12XT300 eye tracker, set to 300 Hz recording speed, at an accuracy of 0.4°13. The eye tracker is connected to a 23-inch Estecom computer screen and was set to a display resolution of 1280×800, at 24-bit color.

We developed the map stimuli following the base map design principles and hazard zone color scheme of the Swiss National Hazard Prediction maps (SFOEN 2016). These area-classed base maps show the probability (of occurrence) and the intensity of potentially occurring natural hazards (i.e., either floods, mass movements, rock falls, or avalanches) in areas with varying hazard risk levels (red = high, blue = moderate, and yellow = low danger).

Figure 1A shows an extract of the official Swiss National Hazard Prediction map series, depicting hazard danger zones in the city of Locarno, in the Canton of Ticino, at the 1:5,000 map scale. Lago Maggiore is located on the right side of the hazard map (Figure 1A), entirely contained in the red and most dangerous hazard zone. Figure 1B is an example of the test stimuli developed for the study following the design of the official Swiss National Hazard Prediction maps (see http://www.sitmap.ti.ch/index.php?ct=pericolie). Areas in the maps with a low risk for natural hazards are assigned to the yellow class. In these yellow areas, the probability and severity of a natural hazard occurring is low. The blue zones are areas with a medium potential of natural hazards occurring with medium intensity. The red class stands for areas where a high probability exists that severe natural hazards could occur (Trau and Hurni

2007). This SFOEN color scheme does not follow standard cartographic practices (i.e., Bertin 1967), the potential implications of which are addressed in the discussion.

The danger zones shown on developed map stimuli (Figure 1B) are reality inspired but not accurate. There are several reasons for this. On the one hand, it is standard practice in Switzerland to employ deterministic models for the calculation of danger zones (Kunz, Grêt-Regamey, and Hurni 2011). The current Swiss guidelines do not include uncertainty information in hazard maps, however. We lack ready-to-use probabilistic models and respective data to generate Swiss hazard maps with accurate depictions of uncertainty (Kunz, Grêt-Regamey, and Hurni 2011). Furthermore, model-based derived hazard zones can result in irregular and complex shapes. We varied the areas and shapes of the danger zones systematically and in a controlled way across stimuli by striking a careful balance between ecological validity and experimental control, as detailed later.

Deitrick (2007) found that local knowledge can bring benefits to map-based decisions. We thus took care to select map stimuli footprints that would not be known to sampled participants. We aimed for map footprints without any labeling. Because most students in the UZH Geography Department are from the German-speaking, eastern parts of Switzerland, especially the Canton of Zurich, we excluded footprints from these regions. We chose footprints from rural regions in predominantly non-German-speaking areas that included small portions of urban zones to avoid recognition, typically near a body of water, a river, or mountainous areas, to include a varied set of hazard danger zones. We selected topographic base maps from the Swiss Federal Office of Topography, swisstopo, available online (see https://map.geo.admin.ch), at the 1:2,500 scale for stimuli creation. To further anonymize the chosen map footprints, we rotated all base maps by 180° (i.e., south up). We delineated hazard risk zones on the chosen base maps by hand, using Adobe Illustrator CS6 (see http://www.adobe.com/products/illustrator.html). We aimed for reality-inspired stimuli, consulting the Swiss National Hazard Prediction maps (SFOEN 2016).

Because there are uncertainties associated with the areal extent of the classed hazard danger zones, we modified the zonal boundaries to show this locational uncertainty using the visual variables of color value, focus, and texture, as proposed and empirically studied in earlier research reviewed previously. We depict uncertainty intrinsically, as proposed by Howard and MacEachren (1996); that is, we communicate data uncertainty directly within the map by means of visual variables. Viard, Caumon, and Lévy (2011) found that this type of uncertainty depiction leads to greater interpretation accuracy for complex questions such as the one that is the focus of our study.

The numbered circles in Figure 2 indicate (1) instructions, (2) the house descriptions including house price and location characteristics, and (3) the map legend explaining the hazard danger levels (all in German).[1] Figure 3 depicts trials that include the depiction of uncertainty. Figure 3 also shows the test question (English equivalent: "Which house would you like to buy?") and response check boxes, labeled A through D.

All risk zone boundaries were selected as center lines to create the uncertainty zones. We manipulated the adjacent zone colors for each visualization type as follows:

- Color value (Figure 3A): Four equally spaced zones, using two shades with decreasing color value for each adjacent color.
- Focus (Figure 3B): Gaussian blurs between the adjacent zone colors.
- Texture (Figure 3C): Four equally spaced zones, using two increasing line sizes and line spacings for each adjacent color.

As mentioned earlier, we also simplified the danger zones and their orientation in the map stimuli, specifically, because vision research suggests that the graphic variables shape and orientation have an influence on visual attention (Wolfe and Horowitz 2004) and because the map-based decision should not be confounded by the shape or orientation of the danger zone.

We developed four prototypical geometry types (horizontal, vertical, branching, and separated zones) where the proportion of the uncertainty zones (relative areas) was held constant across all stimuli. We avoided orientations that might provoke visual illusions (e.g., vertical–horizontal illusions; Gregory 1987) and thus settled for stimuli types presented in Figure 4.

Hedonic house price models developed for Switzerland were perused to include ecologically

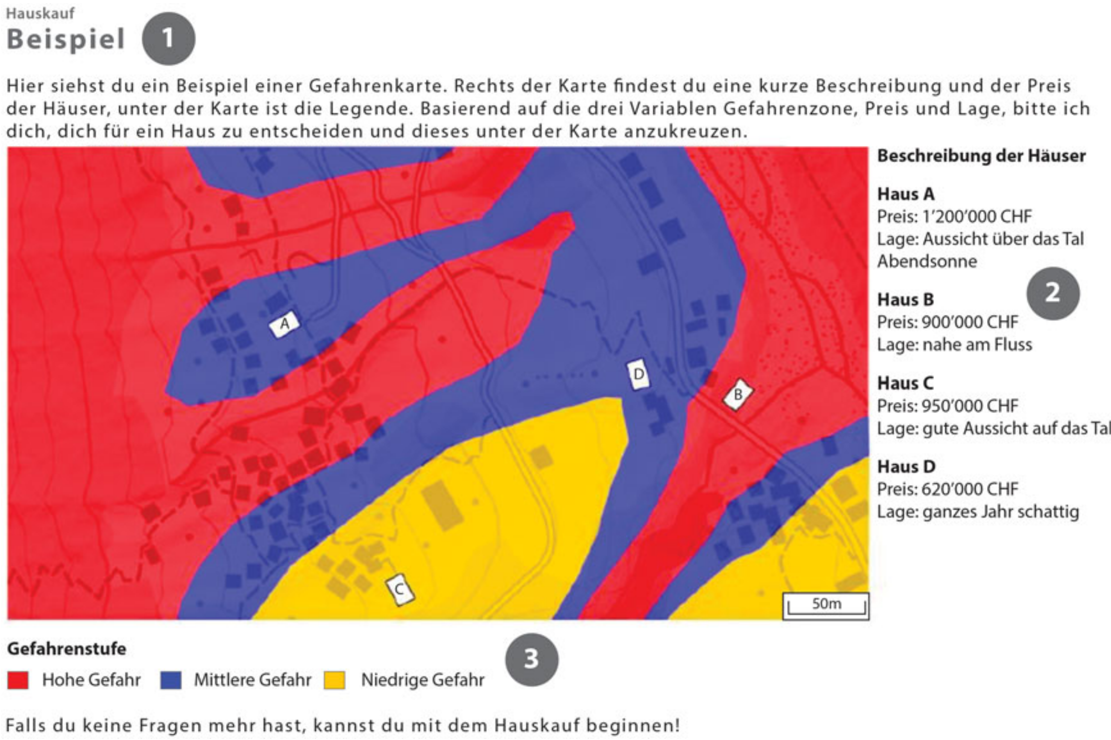

Figure 2. Warmup test stimulus without uncertainty depiction.

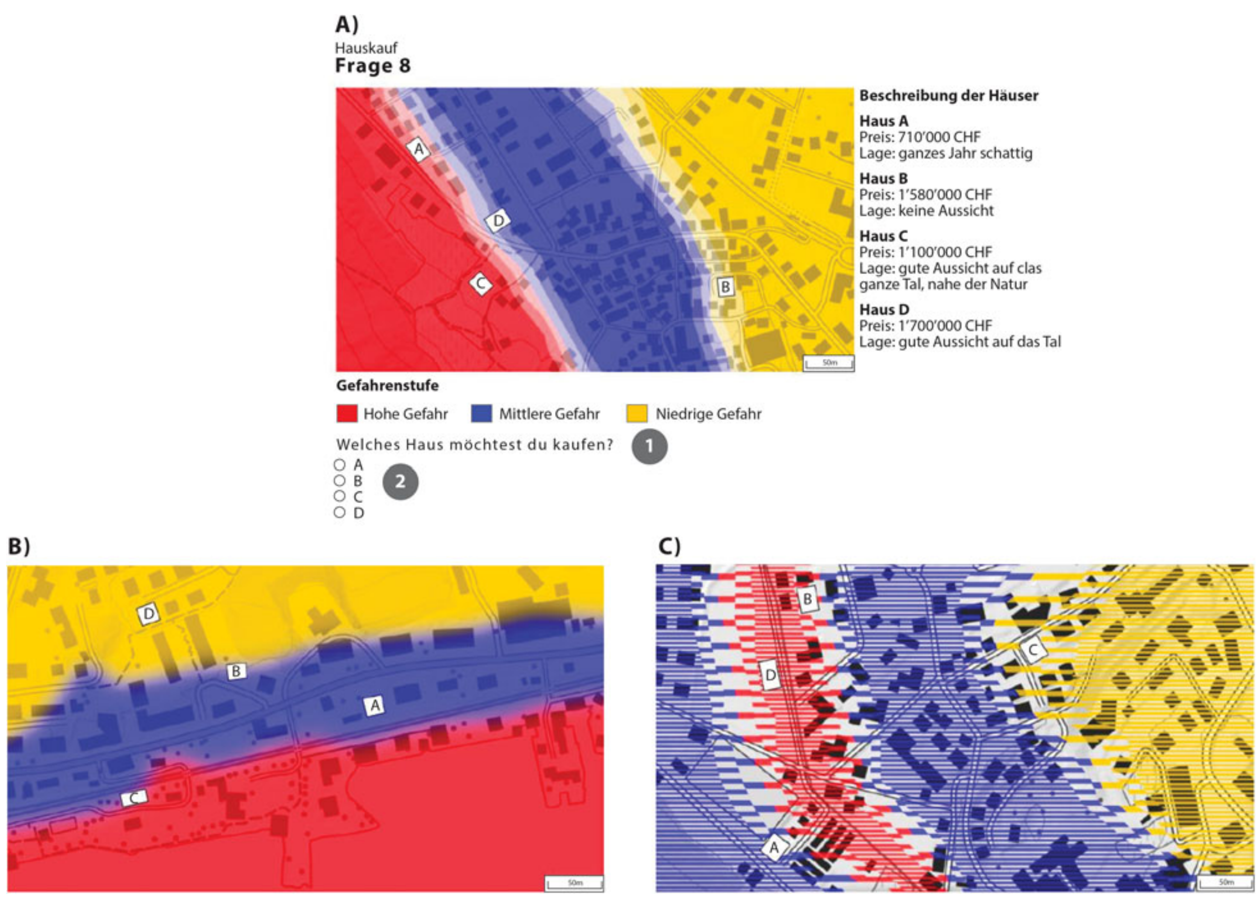

Figure 3. Uncertainty depictions using the empirically tested visual variables (A) color value, (B) focus, and (C) texture to communicate uncertainty at zone boundaries.

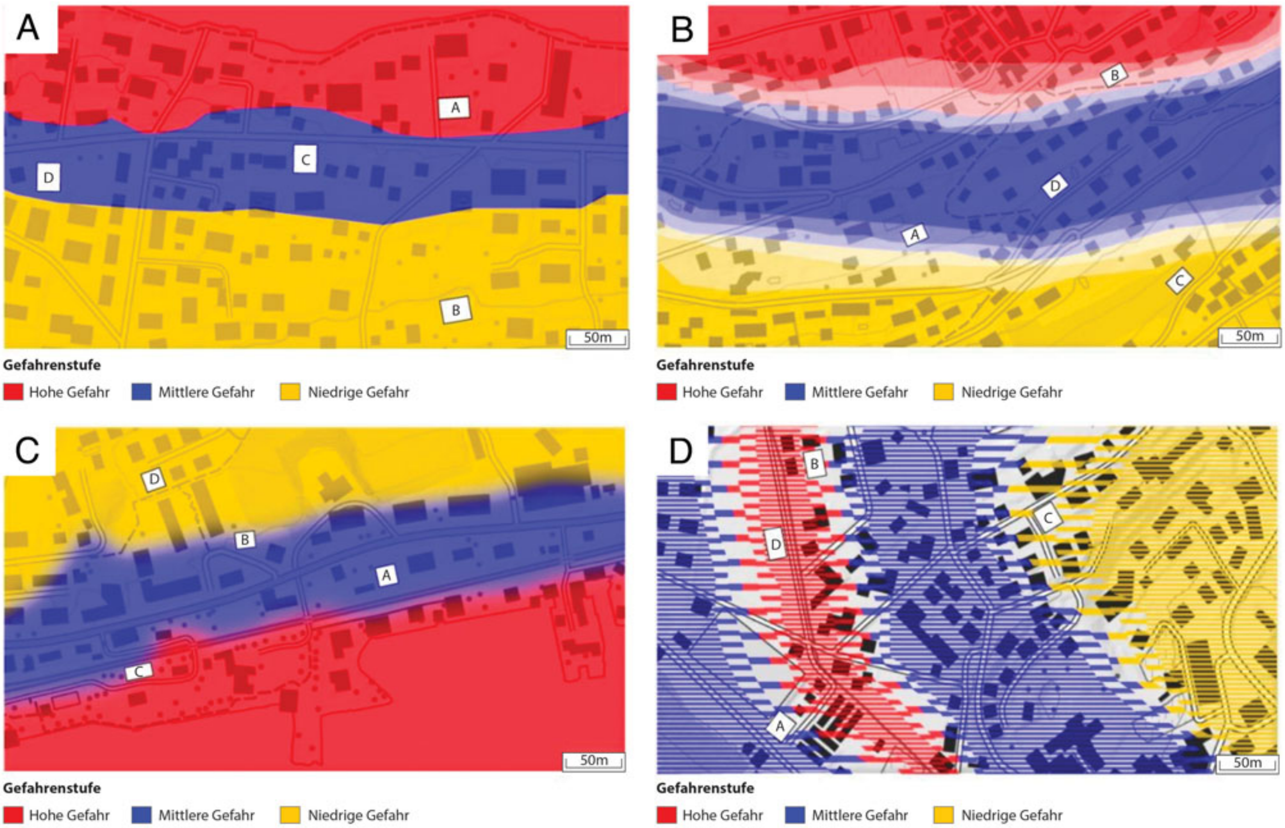

Figure 4. Four examples of the developed geometries shown on stimuli without uncertainty information: (A) horizontal, (B) vertical, (C) branched, and (D) divided zonal arrangement.

valid house characteristics for our chosen house selection scenario (Brühlmann and Leutenegger 2014). For simplicity, and because the participant sample includes nondomain experts, we chose three factors at the ordinal level of measurement: house location (bad– medium–good), house price (low–-medium–high), and hazard risk level (low–medium–high). We chose house aspect or orientation, type of views, and distance to water bodies for the house location descriptions. We developed four combinations including four house types that were jointly shown on any given map stimulus, using a sensible mix of hazard risk, location, and house price. This was intended to ensure that no house would score significantly better on any given trial, because we aimed for a nontrivial house selection task, with no right or wrong decision outcomes. We also took care of systematically varying house locations in the uncertainty zones, considering house labels, house characteristics, and hazard zones. Finally, we systematically rotated house labels (A–D) through the trials, such that a house labeled A in Combination 1 would not always be shown in a red (highest hazard danger) zone, with an attractive house price, and in a less desired location, for instance.

Procedure

The study was carried out during two weeks in May 2016. A pilot study revealed that the experiment could be completed within thirty-five to fifty minutes per participant. The experimenter (the first author) was present in the lab throughout the study. After arriving at the lab, participants were briefed about the study procedure and were asked to sit at a desk to fill out the consent form. The study presented herein was then divided into three phases: pretest questionnaires, map-based main experiment, and posttest questionnaire. At each stage of the study, participants were briefed about the procedure of that phase and could ask questions.

First, participants had to respond to a background questionnaire (including questions about their age, gender, and experience with maps, cartography, GIS, hazard maps, and spatial analysis). This was followed by three standardized questionnaires aimed to assess (1) their risk-taking behavior (Holt and Laury 2002), (2) their spatial thinking skills (Münzer and Hölscher 2011),[2] and (3) their habitual anxiety state (Spielberger, Gorsuch, and Lushene 1970; Laux et al. 1981). We do not report on the habitual anxiety results in this article. All questionnaires were accessible online (see https://onlineumfragen.com/) and presented in the lab on a Lenovo2 T450s laptop with a 14-inch color screen.

This pretest phase was followed by the main, map-based, multicriteria experiment, where we asked participants to make house selections displayed on hazard maps, with or without showing uncertainty at the hazard zone boundaries. For this portion of the study, participants were asked to sit in front of the eye tracker. After calibration with the eye tracker, participants were given the decision-making scenario. Participants were told that they had won a very large sum of money in a lottery and could now fulfill their dream to own a house of their own. To facilitate their decision making, houses available for purchase were going to be presented on a series of maps including hazard danger information.

Participants were told what a hazard map is and what the different zones meant (see Appendix B). They were told that the maps displayed the results of hazard models predicting the risk and extent of natural hazards predicted to occur in the depicted footprint and that these maps were subject to uncertainties. Although participants were given a general clue how to interpret the maps, they were not told that the zone boundaries were uncertain. Furthermore, participants were then told that four houses would be shown on the map, each with a short description of its location and the requested purchase price. Participants were told to select the house they wished to buy, based on the three available characteristics of risk, location, and price. Participants were given a practice trial (shown in Figure 2) using a map without uncertainty information to help familiarize them with the task and the display content (e.g., legend with hazard risk levels, house descriptions, and answer boxes) and the general layout of the test display. Once participants fully understood the task and had no further questions, they could start the main experiment. Participants were not given any time limits for completing this portion of the study. Even though we did record participants' response times, mostly for control reasons, we did not further analyze them, because we were most interested in the type of response and the process of arriving at the response. As mentioned earlier, there were no correct or false answers. Participants were also able to ask questions that did not relate to the interpretation of the map stimuli, if necessary. Participants were not allowed to scroll back to change a decision once made.

Following this second phase of the experiment, participants were asked to complete a posttest questionnaire (see Appendix C), for which they moved back to the desk with the laptop where they had completed the pretest questionnaires. The aim of these concluding questions was to obtain more open feedback from participants on the map-based experiment—decision strategy employed; relevance of the factors location, risk, and price (and other factors) in their decision making; difficulty ratings of the test task—and to assess participants' prior experience in buying a house. To gain a better understanding of participants' decision-making processes, we asked them to describe the strategy they used for selecting their dream home. In this context, we also asked how they interpreted the different depictions of the hazard zone boundaries. The goal of these questions was to understand whether the uncertainty depictions were intuitively understood by participants and to provide process information to interpret measured decision outcomes. Subsequently, participants were asked which of the map stimuli they had seen would best be associated with uncertainty. Other than chocolate and candies, participants were not given any remuneration.

We now turn to decision outcomes of the empirical uncertainty visualization study, ordered by the three study phases described in the procedure section earlier. All quantitative assessments were carried out with SPSS 21 (IBM SPSS Statistics for Windows, Version 21.0, IBM Corp., Armonk, NY, USA).

Results

Decision Outcomes

Thirty-seven participants took part in the study (sixteen women, twenty-one men). Participants' ages ranged between twenty-two and thirty-two years. Except for one person, all participants were students in the UZH Geography Department, either at the bachelor's, master's, or doctoral level. This

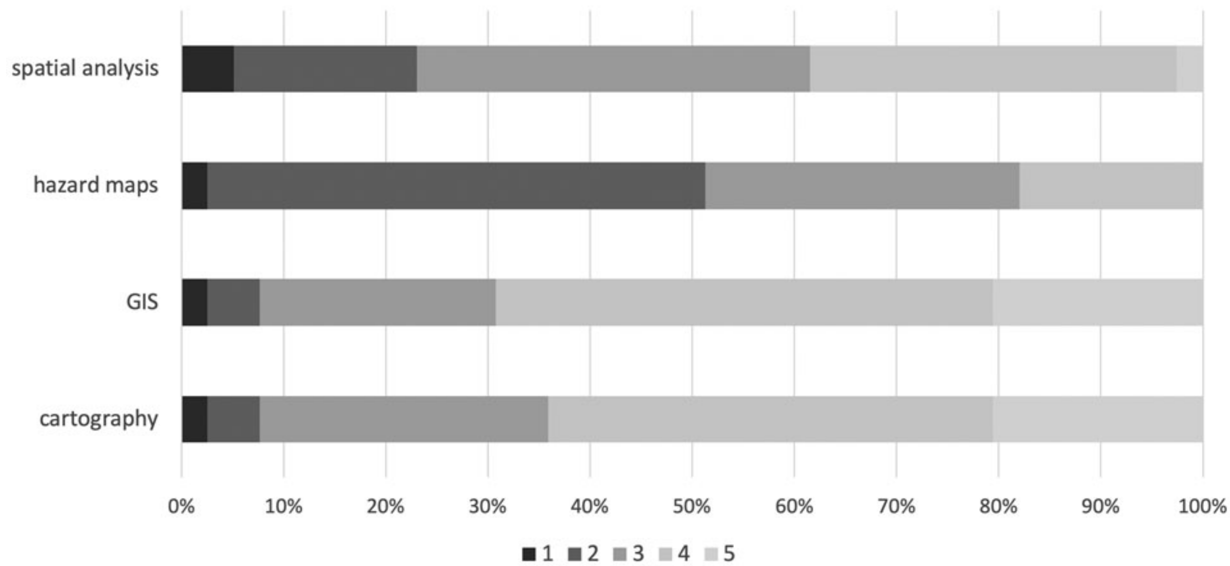

Figure 5. Distribution of participants' experiences, from *very little/none* (1) to *daily/professional* (5): Participants have little domain expertise. GIS = geographic information system.

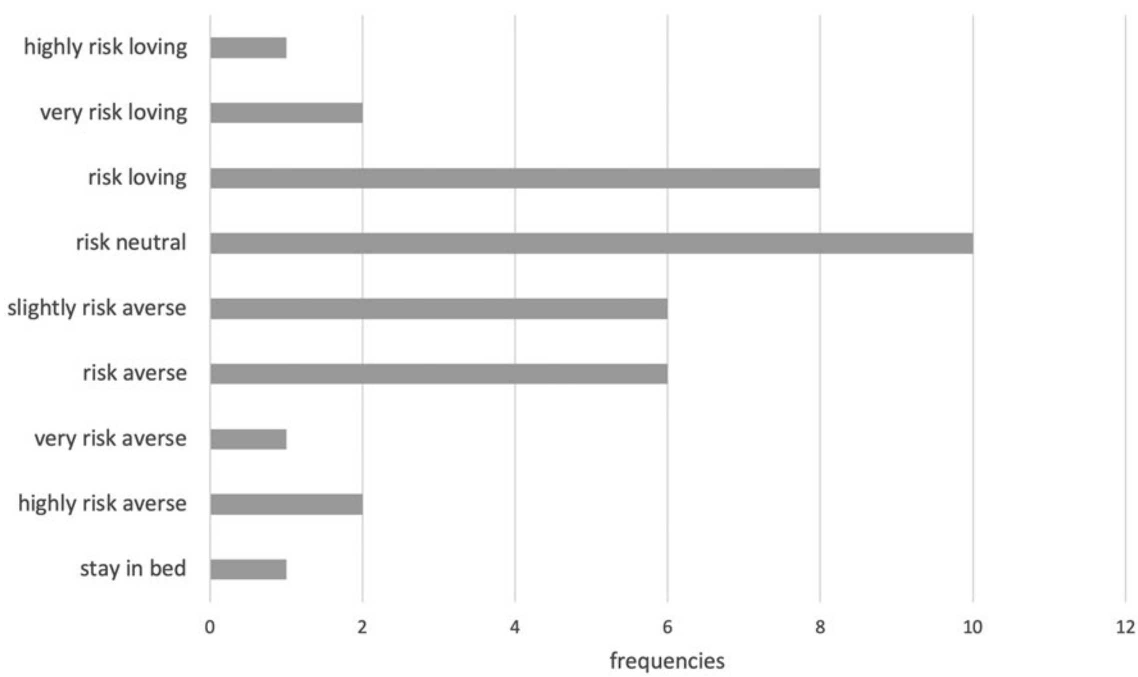

Figure 6. Risk-awareness of participants: Most participants are risk averse.

homogeneous group of participants was the sample we aimed for in this study, as explained earlier.

As expected, participants have experience in cartography, GIS, and spatial analysis (Figure 5). Some of the participants are confronted daily with these topics or deal with these in a professional environment. Conversely, participants have little experience with hazard maps, as intended. We recorded participants' risk-taking attitudes based on a standardized test instrument (Holt and Laury 2002) in a pretest questionnaire. The results are graphed in Figure 6, using the respective categories from Holt and Laury (2002). Sixteen of the participants were classed in the risk-averse category, all categories that are left of the risk-neutral category in Figure 6. Ten participants were classed in the risk-neutral category, and eleven participants were categorized in the risk-seeking categories to the right of the risk-neutral category.

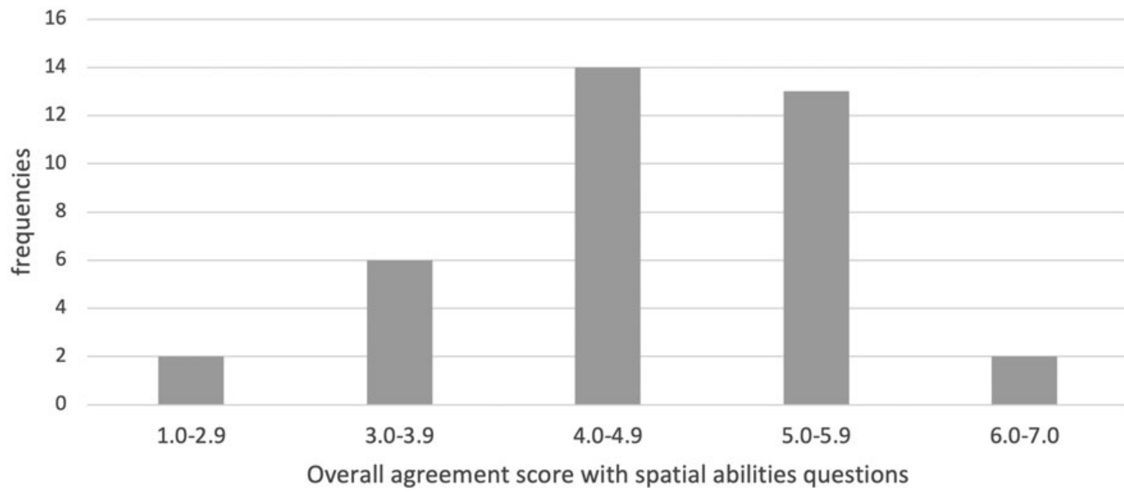

Figure 7. Spatial abilities of participants assessed with the spatial abilities self-assessment instrument: Most participants report having medium to high spatial abilities.

Figure 7 depicts average overall spatial ability ratings of the participants based on the German spatial abilities test (Münzer and Hölscher 2011)—based on the Santa Barbara Sense of Direction Test. The higher the average score, the better the self-reported localization and navigation ability of the individual participants. An average score between 1.0 and 2.9 means that self-assessed spatial ability is very low. Conversely, averaged self-assessed ability scores from 6.0 to 7.0 mean that those participants considered their spatial ability as very high. In general, our participant sample considered themselves to have good self-localization and navigation skills. The overall average score of the sample is 4.67 ($SE = 0.18$) and thus considered of average spatial ability. Even though the range is relatively large (1.84–6.89), we can generally assume that most participants assessed their spatial abilities as average to high.

We now turn to the results of Phase 2, the map-based decision-making portion of the experiment. We first present the results of the decision outcomes as one indicator of decision-making performance. We also report outcomes based on participants' risk-taking behaviors. Self-reported spatial abilities did not matter in this experiment. As we saw earlier, most participants indicated having average spatial abilities and thus we omit reporting these results. As mentioned earlier, there were no correct or false answers in the experiment. Participants could freely choose the house that best suited their needs. The focus of our analysis is thus to examine whether participants' decisions would be influenced by the different depictions of the hazard danger zones: Without any uncertainty information or with uncertainty information depicted intrinsically at the hazard danger zone boundaries, by either color value, focus, or texture.

Table 1. Classification of house choices

House type	Hazard danger	Location	Price
1	Yellow/blue	Poor	Low/medium/high
2	Yellow/blue	Medium/good	Low/medium
3	Yellow/blue	Medium/good	High
4	Red	Poor	Low/medium/high
5	Red	Medium/good	Low/medium
6	Red	Medium/good	High

For the quantitative analysis, we first needed to preprocess responses to be able to comparatively assess participants' choices. We classed houses into six house type (HT) responses, as shown in Table 1. This reclassification is based on observed participant behavior and their feedback on the decision-making process reported in the posttest questionnaire. We reclassed the hazard danger zones from initially three classes (red = high, blue = moderate, and yellow = low danger) to two classes as shown in the second column in Table 1. We collapsed the low (yellow) and medium (blue) danger zones to more clearly distinguish these responses from those of the high hazard risk areas. Participants reported in the posttest questionnaires that they perceived the difference between these two lower hazard risk zones to be less than between the blue and the red zones, at opposite ends of the hazard risk spectrum. Also, according to

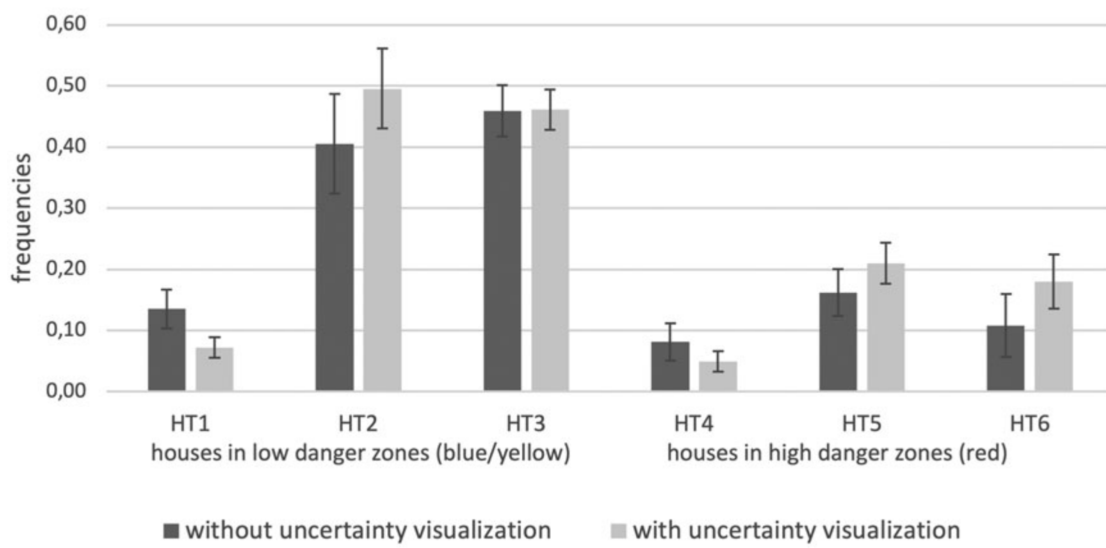

Figure 8. Average normalized frequencies of chosen HTs, *SE* = ±1. HTs 2 and 3 are selected most, independent of uncertainty visualization. HT = house type.

their reports, several participants (categorically) excluded houses in the red zone and only considered buying those in the yellow and blue zones. Thus, we conclude that the red zone was perceived differently from the yellow and blue zones.

We reclassed the houses based on the location criteria from initially three classes into two classes. Houses in a poor location were characterized with negative connotations, whereas both those in medium and good locations had characteristics with positive connotations. The language used might lead participants to perceive poor location characteristics as clearly different from the other two. Indeed, several participants reported having categorically excluded houses in a poor location, irrespective of price or hazard risk zone. That is, as we see later, house location was perceived to be the most decisive factor in participants' decision making. It seems that house price did not play a decisive role for houses in unattractive locations. Only for those houses in medium to good locations did price seem to have mattered; some participants reported excluding houses perceived to be too expensive. Hence, except for the houses with poor locations, we thus decided to reclass the house price categories from the initial three classes (low– medium–high) to only two classes (low/medium and high), with the aim of gaining clarity in the response pattern. We thus assigned each house to one of the six classes listed in Table 1.

To be able to analyze the categorical house choices statistically, we transformed participant responses into normalized frequencies. The frequency with which a type of house was selected was divided by the number of times a type of house was available for selection for each participant for a given visualization type. For example, if a participant chose HT 3 two times for maps without visualization of uncertainty and that house type was available five times on these maps, the normalized frequency for HT 3 is $2/5 = 0.4$ for maps without uncertainty visualization for this participant. This number is equal to a selection percentage. In other words, this participant chose HT 3 in 40 percent of the maps without the visualization of uncertainty.

The house selections are graphed in Figure 8. Clearly, HTs 1 and 4 are least frequently selected for both uncertainty depiction conditions. These house types are at an unattractive location. Conversely, most frequently selected HTs 2 and 3 are in a low-risk zone and have a medium/good location. These houses are ranked low/medium (HT 2) and high (HT 3) on the house price scale. The combination of low risk and medium/good location is thus popular with the participants. House types 5 and 6 also have a medium/good location. These houses were chosen less often than types 2 and 3, probably because they are in a zone with a higher hazard danger. Interestingly, HTs 5 and 6 seem to be somewhat more popular in the trials with depicted uncertainty compared to those without.

The statistical assessment of summed frequencies per house type aggregated across maps without the visualization of uncertainty and the maps with the visualization of uncertainty did not yield any

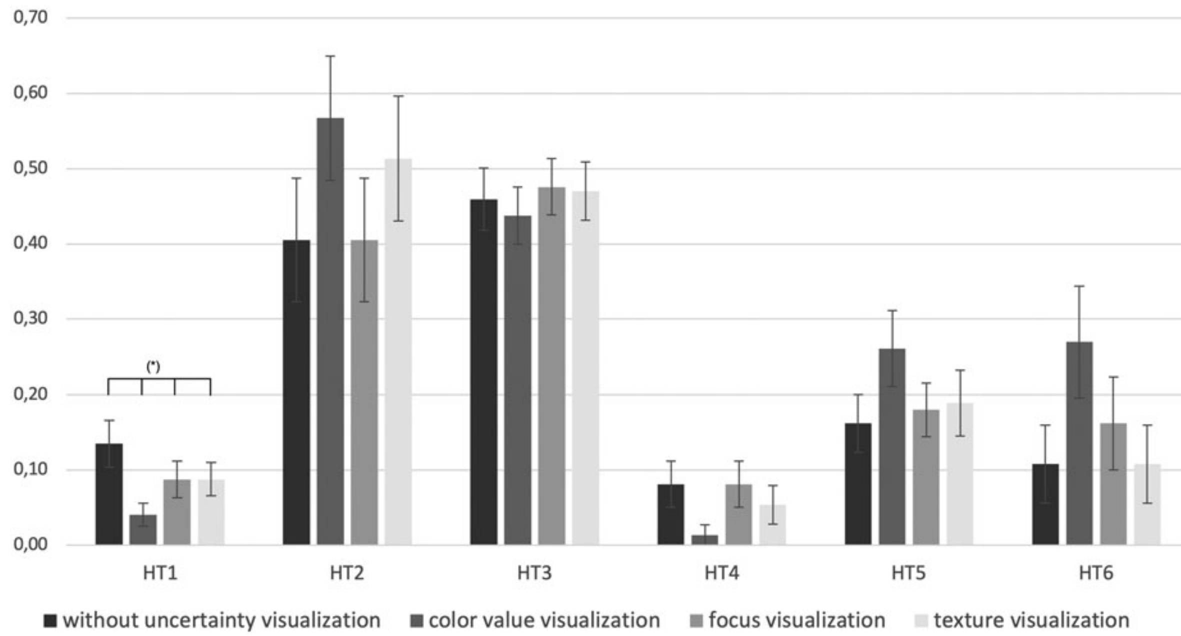

Figure 9. House type scores across visualization types (average frequencies, ±1 *SE*). The asterisk denotes a possible significant difference ($p < 0.05$). HTs 1 and 4 are selected least, but frequencies differ across uncertainty visualization types. HT = house type.

significant differences. We then looked more closely at the types of uncertainty visualizations (Figure 9), another of our controlled variables.

The overall popularity pattern of the chosen house types follows the pattern seen in Figure 9. For those trials where uncertainty is depicted by color value, houses with unattractive locations (HTs 1 and 4) are much less popular compared to the other trials. Conversely, HTs 5 and 6, which have a medium/good location but are also located in the red hazard danger zone, seem to be more popular when displaying uncertainty with a color value than with the other uncertainty visualization methods. We uncovered a potentially significant difference in the average house choice frequencies across uncertainty visualization types by means of an omnibus Friedman test. At closer inspection, though, using a Bonferroni-corrected post hoc test, the significance for HT 1 disappears: HT 1: $\chi^2(3) = 8.444$, $p = 0.038$; HT 2: $\chi^2(3) = 4.629$, $p = 0.201$; HT 3: $F(3) = 0.438$, $p = 0.727$; HT 4: $\chi^2(3) = 5.743$, $p = 0.125$; HT 5: $\chi^2(3) = 4.943$, $p = 0.176$; HT 6: $\chi^2(3) = 5.760$, $p = 0.124$. We thus treat this particular result with caution.

From these detailed results it seems that the visualization of uncertainty has indeed influenced participants' decision making. Counterintuitively, it appears that participants more frequently selected houses in the red danger zone when uncertainty information was depicted. In other words, the visualization of uncertainty makes houses in a red danger zone more attractive. We thus analyzed the response data in the twelve trials that contain only uncertainty depictions and tallied the number of times a participant chose a house in a more certain zone (outside the uncertainty boundary) and the number of times a house was selected in an uncertain zone (within the uncertainty boundary). The maps without visualization of uncertainty were not considered in this analysis.

Figure 10 suggests that participants more frequently chose houses located in the uncertainty zone within a hazard danger area. In fact, the average selection frequency for houses in more certain locations is 4.68 ($SE = 0.32$), and for houses in uncertain locations it is 7.32 ($SE = 0.32$). In other words, in the twelve maps that contained uncertainty depictions, an average of 4.68 houses were selected from within a more certain hazard zone and 7.32 from within an uncertain (boundary) zone. This difference is significant, $t(36) = -4.083$, $p = 0.000$. This response pattern is identical across all uncertainty visualization types (i.e., for color value, focus, and texture). The data reported here cover all uncertainty zones; that is, houses located in an uncertain red, blue, or yellow zone. The result pattern is also similar if we only look at differences between the number of times houses were selected in a certain red hazard zone ($M = 0.92$, $SE = 0.21$), compared to

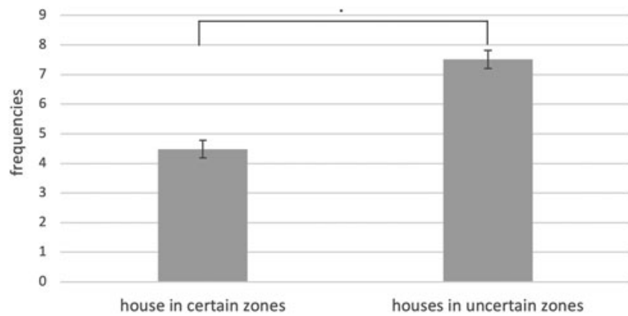

Figure 10. House selection frequencies across uncertainty zones irrespective of the risk class. Houses in uncertain locations are selected more frequently.

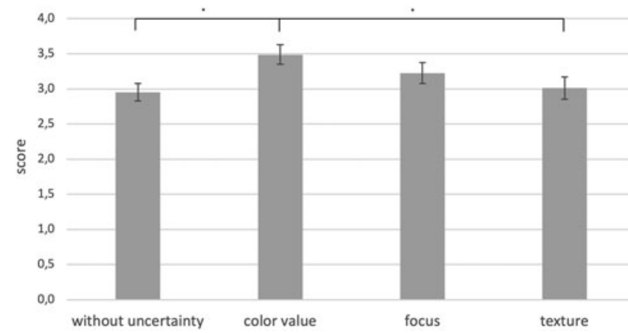

Figure 11. Risk-taking scores across uncertainty visualization types. Risk seekers make riskier house choices with visualized uncertainty.

houses that are in an uncertain (boundary) red hazard zone ($M = 1.81$, $SE = 0.23$). This difference is significant ($z = -2.838$, $p = 0.005$); houses in an uncertain red hazard (boundary) zone were selected twice as often as houses in a certain red hazard zone.

As mentioned earlier, we also considered individual differences between the decision makers in our investigation (i.e., spatial ability and risk-taking behavior), a truly unique feature of our uncertainty visualization study. We divided participants into risk-averse ($n = 16$) and not risk-averse groups (i.e., risk neutral [$n = 10$] and risk seeking [$n = 11$]; total $n = 21$), based on their risk-taking behavior scores, assessed with the Holt and Laury (2002) instrument described earlier (see Figure 6).

Compared to the risk-averse group, where we did not find any significant differences, the average house choice score across trials seems to change across uncertainty visualization methods when risk-seekers make decisions (see Figure 11). The omnibus test shows a significant difference in the average scores for risk-takers across all trials, $F(3.60) = 4.054$, $p = 0.011$. The post hoc tests reveal that the average scores differ between the maps without any uncertainty depiction and the trials with uncertainty depictions using color value. Also, the difference between the uncertainty depiction types color value and texture are significant. This indicates that the risk-seeking group chooses different houses, depending on whether uncertainty was shown with color value, texture, or not at all. Given that the score is highest for the trials with a color value, this could mean that risk-seekers were more likely to select a house in the highest (red) hazard danger zone when uncertainty was visualized with color value. As already mentioned, spatial ability measured with the German version of the Santa Barbara Sense of Direction Test (Münzer & Hölscher 2011) did not appear to matter in our study.

The Decision-Making Process

Finally, and most important, we wished to investigate participants' decision processes more deeply, considering the available factors of house location, hazard risk, and house price. For this, we developed an explanatory model by means of a binary logistic regression. The model is set up such that we ask this: Which characteristics must a house have to be selected with higher probability? We assigned the dependent variable house selection a value of zero if the house is not selected and a value one if the house is selected. The independent variables in our model represent the different house characteristics: house location, house price, hazard risk zone, and uncertainty of the hazard zone. For the sake of simplicity, we also used binary characteristics of the independent variables. Table 2 shows the characteristics of the individual variables and their meaning for the model.

As already mentioned, a unique feature of our study is the consideration of the human factor in the decision-making process; we thus included the risk-taking behavior of the participants as an additional binary predictor in our binary logistic regression model. For risk-averse participants we assigned a value of zero and for risk-seekers a value of one. We assigned the respective values for the model using the data we collected for each trial and for all participants. We submitted the preprocessed response data to a binary logistic regression to further analyze participants' decision-making processes by means of an explanatory model. We selected a step-wise, forward selection method with a likelihood quotient, recommended for exploratory studies (Field 2009). Table 3 summarizes the computed binary logistic regression model including all visualization types. The first

Table 2. Variable definition in our binary regression model

Value	Hazard danger zone	Location	Price	Uncertainty
0	Low (yellow | blue)	Poor	Low	No
1	High (red)	Medium/ good	Medium/ high	Yes

Table 3. Model output for trials across all visualization types

		95% Confidence interval odds ratio		
Variables	*B* (*SE*)	Lower limit	Odds ratio	Upper limit
Constant	−2.02 (0.12)			
Location	2.17* (0.14)	6.70	8.76	11.43
Danger zone	−1.37* (0.12)	0.20	0.26	0.32

Notes: $R^2 = 0.17$ (Hosmer and Lemeshow), 0.18 (Cox and Snell), 0.26 (Nagelkerke), model $\chi^2 = 431.73$, $p < 0.05$.
*$p < 0.05$.

column lists the variables location and danger zone that are kept in the model and thus have a significant influence on the house selection process. The second column displays the beta values of the remaining variables in the model and their respective standard errors. Using these values, we can compute the probability that a house is selected based on the variables of location and danger zone.

Tables 3, 4, and 5 indicate how the odds of a house being selected change when the independent variable increases or decreases by one unit (Field 2009). If the value of this ratio is greater than one, then the chance that participants selected a house increased when the assigned value of an independent variable increased. Hence, if the value of the location variable is one (medium/good location), then the chance of this house being selected by our participants increased. Conversely, if the odds ratio is less than one (as it is for the danger zone in Tables 3, 4, and 5), this means that an increase in the independent variable by one unit decreases the chance of this house being selected. Hence, if the hazard danger zone is set to one (indicating a high hazard danger), the chance of the house being selected decreases, as expected.

The model output for the trials that contained only uncertainty depictions (Table 5) suggests that, indeed, uncertainty of the hazard risk boundary zone played a role in the decision-making process. More important, however, the likelihood for house selections based on the variables of location and risk danger zone increased even more, compared to the trials without uncertainty (Table 4).

Using standardized model coefficients, we can directly compare house selection likelihoods based on all trials or across trials with or without uncertainty depictions. In summary, our results show that, if a house has a medium/good location and is located in a lower hazard risk zone, the probability that this house was selected by our participants over all trials is relatively high. Table 6 also suggests that location has a greater influence on this decision (larger standardized coefficients) than the danger zone in which a house is located. We discover the same response pattern when separating trials with uncertainty from without uncertainty depictions. When uncertainty is shown in the map display, it is indeed considered by participants in their decision making. Interesting, if uncertainty is depicted, overall, this (weakly) increases the odds that a house is selected. We also see this effect in Figure 10.

Discussion

We set out to investigate whether the visualization of uncertainty and how it is visualized would influence decision outcomes of nondomain experts by means of a map-based multicriteria house selection task. This task considered house price, house location, and natural hazard dangers, without right or wrong decision outcomes. We found that participants indeed change their house selection decisions dependent on whether uncertainty is shown or not. This replicates Cheong et al.'s (2016) and Leitner and Buttenfield's (2000) findings for different decision-making contexts.

This outcome is particularly notable for house types that, overall, are least popular due to undesired location characteristics. The location of a house turned out to be one of the most decisive selection factors, according to a binary logistic regression model we developed to study participants' decision-making processes. Unpopular house locations are even more unpopular when uncertainty is visualized with the visual variable of color value. The importance of the house location and hazard danger zone factors changes when maps include uncertainty information. For maps without the visualization of uncertainty, the hazard danger is the most important

Table 4. Model output for trials without uncertainty suggests that the factor's location and danger zone play the most important role in participants' house selections

		95% Confidence interval odds ratio		
Variables	*B* (*SE*)	Lower limit	Odds ratio	Upper limit
Constant	−1.37 (0.19)			
Location	1.37* (0.23)	2.51	3.93	6.15
Hazard risk zone	−1.06* (0.22)	0.22	0.35	0.53

Notes: R^2 = 0.10 (Cox and Snell), model $\chi^2 = 55.16$, $p < 0.05$.
*$p < 0.05$.

Table 5. Model output for trials with uncertainty reinforces participants' house selection criteria

		95% Confidence interval odds ratio		
Variables	*B* (*SE*)	Lower limit	Odds ratio	Upper limit
Constant	−2.53 (0.17)			
Location	2.52* (0.18)	8.76	12.38	17.50
Hazard risk zone	−1.46* (0.14)	0.18	0.23	0.31
Uncertainty	0.35* (0.13)	1.10	1.42	1.82

Notes: R^2 = 0.21 (Cox and Snell), model $\chi^2 = 403.67$, $p < 0.05$.
*$p < 0.05$.

Table 6. Comparing participant choices across trial types

Overall model		Without uncertainty depiction	
Variables	Standardized coefficients	Variables	Standardized coefficients
Location	$2.17 \times 0.14 = 0.30$	Location	$1.37 \times 0.23 = 0.32$
Hazard risk zone	$-1.37 \times 0.12 = -0.16$	Hazard risk zone	$-1.06 \times 0.22 = -0.23$
		With uncertainty depiction	
		Location	$2.52 \times 0.18 = 0.45$
		Hazard risk zone	$-1.46 \times 0.14 = -0.20$
		uncertainty	$0.35 \times 0.13 = 0.05$

factor, whereas for maps with the visualization of uncertainty, house location characteristics were perceived to be more important by our participants.

In fact, participants significantly more often opted for a house in an uncertain zone, regardless of the hazard danger level or other factors, irrespective of the visualization type. Based on prior work by Hope and Hunter (2007a), one would expect the opposite results. These authors found that when visualizing uncertainty represented by a clearly visualized uncertainty boundary zone, decision makers take less risk. The authors posited that crossing a given line or zone boundary is perceived to be a hurdle (Hope and Hunter 2007a). In contrast, they found that decision makers are prepared to take more risk in trials where an uncertainty border zone is not visible. Based on this, we expected similar results. When using color values, the uncertainty boundary zone is especially salient, so we expected participants to make less risky decisions. Participants, however, most often chose houses in the riskier and highest ranked (red) hazard danger zone when uncertainty was visualized with color value. Based on loss aversion theory (Kahneman 2011), one would expect the opposite. That is, a decision maker would perceive the possibility of house loss due to increased hazard danger to be greater than the possible gain of an attractive location or a low price. For this reason, it seems more sensible for our participants to choose the more certain and thus less risky option. An alternative explanation for this result could be that the depicted uncertainty at hazard zone boundaries might have suggested to participants not to trust the official hazard zone classification at all, given that the zone boundaries are uncertain. Indeed, as Table 6 suggests, when the model includes the uncertainty variable, the odds decrease even further that a house is selected by our participants, compared to trials without uncertainty depiction. This might explain why they gave it less weight in the decision-making process.

Although self-reports suggest that most participants did intuitively understand that the chosen visual variables represented uncertainty, as prior work would predict (e.g., Leitner and Buttenfield 2000; MacEachren et al. 2012), it also seems that color value must have especially confused our participants. One explanation could be that because the map included hazard danger predictions, they might have misinterpreted the lighter color shades to mean less occurrence of hazard danger or risk, instead of less certainty in the location of the danger hazard zone boundary. In fact, sampled geography students were exposed to cartographic theory in their course work, which suggests that lower magnitudes of variables, mapped with value-by-area maps, should be visualized by lighter color shades (Bertin 1967). In contrast, in trials where the visual variable focus is used to denote uncertainty, the boundary zone is less clearly marked. According to Hope and Hunter (2007a), this should lead participants to make riskier decisions, which we could not confirm in our study. In fact, participants making house choices with maps that depict uncertainty with the focus variable yielded decision outcomes with lower average scores compared to those who selected houses with maps showing uncertainty with color value. This suggests that, on average, fewer houses were selected in the red (highest) danger zone when uncertainty was visualized with focus.

These results raise the question of whether and how the depiction of uncertainty might have influenced the perception of hazard danger and risk. One interpretation could be that hazard danger was underestimated in the trials with the visualization of uncertainty, because participants more often selected houses in the highest hazard danger zone. Participants' house buying task inexperience could have played a role. Similarly to Roth's (2009) study, nondomain expert participants underestimate hazard danger. Roth suggested that experts are more used to dealing with uncertainty and thus they probably do not underestimate danger as much as nonexperts. Aside from expertise, the perception of hazard and risk might have been influenced by the visual properties of the display (Ash, Schumann, and Bowser 2014). Our study reflects results by Ash, Schumann, and Bowser (2014) in the context of uncertainty depictions of tornado landfall predictions. Risk perception of participants changed due to different visualizations of the cone of uncertainty of the predicted tornado path. Participants perceived a greater tornado risk without cone of uncertainty depiction; they felt less need to protect themselves from tornadoes when the cone of tornado uncertainty was depicted by a color value. When uncertainty was depicted by a color hue, they felt less danger (Ash, Schumann, and Bowser 2014). Similar to the results of Ash, Schumann, and Bowser, our participants seem to have underestimated hazard risks with the visualization of uncertainty, because they most often selected houses in the red danger zone in trials showing uncertainty with a color value. It could also be conceivable that some of our participants trained in cartography might have misinterpreted the colors, even though all participants were given ample time to study the test materials, had to go through a warmup trial before the main experiment, and all map stimuli featured a detailed legend. Both house selection results and self-reports of participants describing their selection strategies, however, confirm conscious choices of considering houses in the highest danger zone only when they were in the uncertainty boundary zone. Given these replicated results, one might wonder whether to suggest the visualization of uncertainty for nondomain experts, especially when natural hazards are visualized. One the one hand, participants did not perceive the visualization of uncertainty as an additional complexity, thus replicating Leitner and Buttenfield's (2000) findings, and they obviously included it as a decision support. On the other hand, uncertainty depiction styles should be developed carefully to avoid misinterpretation of hazard danger.

A second objective of our research is to better understand the map-based decision-making process when zonal uncertainty is depicted at zone boundaries in different ways. As reviewed earlier, the decision science literature suggests that heuristic approaches to decision making under uncertainty (Kahneman 2011) have rarely been studied in a map-based multicriteria context (Keuper 2004; McKenzie et al. 2016; Ruginski et al. 2016). Similar to Keuper's (2004) multicriteria study, we found that participants' decision heuristics are indeed influenced by whether and how uncertainty information is visualized. This influence has also been found in decision-making contexts with low complexity related to the uncertainty of linear features (hurricane paths) and point features (locational accuracy of Global Positioning System fixes; McKenzie et al. 2016; Ruginski et al. 2016).

Based on our logistic binary regression models, we suggest that our nondomain experts likely employed a weighted additive heuristic, dependent on (1) whether uncertainty was visualized or not and (2) how it was visualized, by assigning available decision criteria a different importance. The most important factor in participants' decision-making heuristics is the house location characteristic, independent of visualization. If uncertainty is visualized, location characteristics become even more important, and the hazard risk zone is slightly less important. As hypothesized, this might be the result of participants' changing risk perceptions, due to changed uncertainty depiction styles, as previously explained. Alternatively, the additive weighted heuristics could have been mixed with an "elimination of alternatives" heuristic, as suggested by Payne, Bettman, and Johnson (1993) for non-map-based decision-making contexts. With this eliminatory heuristic, the most important criterion and a respective threshold value are first determined by decision makers. All decision alternatives that do not meet the criterion's threshold are eliminated in the order of importance, leading to one specific decision. Based on posttest self-reports, some participants explicitly mentioned a decision strategy excluding houses that did not meet certain criteria; for example, houses that did not meet a desired location criterion or were located in a high hazard danger zone.

A specific feature of our map-based decision-making study is the additional consideration of the decision maker's background, attitude, and training. As a novel outcome of our study, we discovered that participants make predicable decisions based on their risk-taking attitude. Risk-seekers made riskier choices, and this was facilitated by the uncertainty visualization method. Because we already know from the general empirical cartographic literature that experience and training play a significant role for many map-based decisions, we specifically controlled for experience by including nondomain experts. Because hazard danger lost its importance as a decision criterion, specifically in trials that included the visualization of uncertainty, we contend that nondomain experts might have underestimated the risk or hazard of a natural disaster. This is probably due to their lack of experience in dealing with uncertainty in the assessment of natural hazards, as Roth (2009) suggested.

Conclusions and Outlook

For a long time, humans have made important and relevant space–time decisions using geographic information displayed on maps. The spatial data on which our space–time decisions are based are subject to uncertainties. These uncertainties can be visualized, which, in turn, can influence decision outcomes. To better understand how a complex decision is made with the help of a map on which uncertainty is visualized at class boundaries, we conducted an empirical study with thirty-seven participants, none of whom was a domain expert for the given decision-making scenario of choosing a house to buy based on an area-classed hazard map display. Our results show that the depiction of uncertainty at the class boundaries is understood as such by our participants in principle but their interpretation of the depicted uncertainty is partly counterintuitive and surprising. Using visualizations with uncertainty led them instead to choose more houses in risk-prone areas than using visualizations without uncertainty depiction. We take this as a clear indication that further research is needed to better understand the influence of uncertainty depiction in complex decision-making scenarios and that uncertainty depiction styles need to be carefully developed to avoid their misinterpretation. This research might also provide further incentives to consider alternative visual methods that still need to be developed that might support people to reason about uncertainty more effectively and efficiently.

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Notes

1. Translations of the German text in Figures 2 and 3 are available in Appendix A.
2. This is a German-language spatial abilities test based on the Santa Barbara Sense of Direction Test by Hegarty et al. (2002).

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Appendix A: Translation from German into English of the Material Used in the Study, as It Is Depicted in the Main Text

Figure 2.

1. Here you can see an example of a hazard risk map. To the right of the map you will find a short description and the price of the houses; below the map is the legend. Based on the three variables—danger zone, price, and location—I ask you to select a house and mark it below the map.
2. House descriptions

- House A

Price: 1,200,000 CHF
Location: Valley view, evening sun

- House B

Price: 900,000 CHF
Location: Near a river

- House C

Price: 950,000 CHF
Location: Good valley views

- House D

Price: 620,000 CHF
Location: Shady throughout the year

1. Hazard risk level
    - High risk
    - Medium risk
    - Low risk

If you don't have any more questions, then you can begin with the house purchase!

Figure 3.

1. Which house do you wish to purchase?

House descriptions

- House A

Price: 710,000 CHF
Location: Shady throughout the year

- House B

Price: 1,580,000 CHF
Location: No view

- House C

Price: 1,100,000 CHF
Location: Good view over the entire valley, near nature

- House D

Price: 1,700,000 CHF
Location: Good view over the valley

Appendix B: Instructions Given to Participants before the Warmup Trials and before the Main Portion of the Experiment (Translation from German into English)

Scenario

Imagine you played the lottery last week and just learned that you won a large sum of money. You are now able to afford many things that were not possible before. For a long time you wished you were able to buy a house. This is now possible. Congratulations!

While you have already decided on certain regions, you have not settled yet for specific towns in which you wish to buy your house. As you are still undecided, and the selection of available houses is large, your decision is supported by various maps. On each of these maps, there are four houses for sale. Your task is to choose one of these available houses to buy.

Your decision will not be based on a traditional map but rather a hazard risk map. In a hazard risk map, the footprint is divided into three classes. These classes represent the probability and likelihood of a natural hazard occurring in this area. Possible natural hazards include floods, avalanches, and debris flows. The yellow class represents areas with a low natural hazard risk. In these areas, the probability of a natural hazard occurring and its severity are low. The blue zones represent areas with a medium hazard risk. The red class is assigned to areas in which there is a high probability of severe natural hazards occurring. The following Figure B.1 should help you to better understand the classification.

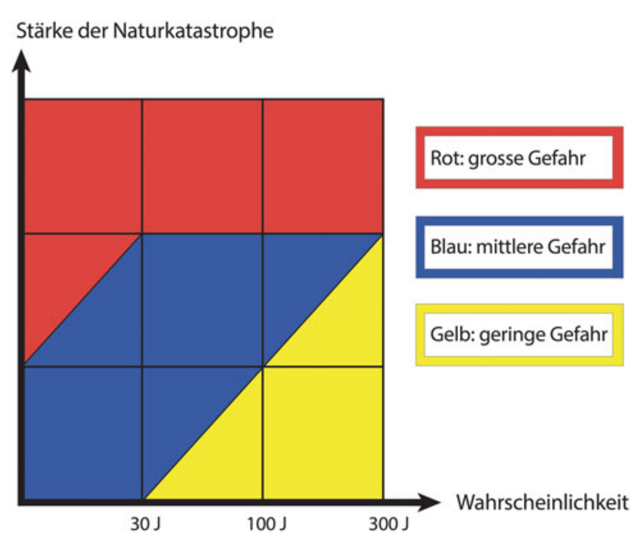

Figure B1. *Source:* Trau and Hurni (2007).

Label, y-axis: Severity of the natural hazard
Label, x-axis: Probability
Boxes: Red, great danger; blue, medium danger; yellow, low danger

Many qualitative and quantitative models are used to create these classes. Thanks to these models, it is possible to simulate and predict natural hazards in all areas of Switzerland. Hence, it is possible to define which areas are less affected by a natural hazards and which areas are more strongly affected. The models, and therefore also these hazard predictions, and the maps themselves always contain uncertainties, however.

The hazard map not only shows the position of a house and in which hazard risk zones it is located but it also contains a short description of the location and its purchase price. Based on these three characteristics:

- Risk
- Location
- Price

I ask you to choose the house that you like best. In the following you will see sixteen maps on your computer screen. Your task will be to choose one house per map that you would like to buy, based on the information presented here. Imagine that the houses are all of the same size.

If you have no further questions, you can scroll to the next page. There you will find an example of the task you are going to perform.

Appendix C: Questions We Asked Participants in the Posttest Questionnaire

This questionnaire was originally given in German. An English translation is provided here for convenience. Participants answered this questionnaire question by question. This means that they did not see the next question until the current question was answered.

Q1: Welcher Aspekt war für dich am wichtigsten bei deiner Entscheidung für den Hauskauf? Positioniere zu oberst den Aspekt, welcher für dich am wichtigsten war und zu unterst den unwichtigsten Aspekt.

[Which factor did you deem most important in selecting a house to buy? Please list the most

important factor on top and the least important factor at the bottom.]
Q2: Hast du noch andere Aspekte (z.B. Strassen) bei deiner Entscheidung berücksichtigt? Wenn ja, liste bitte diese Aspekte hier unten auf.
[Did you take into account any other factors (e.g., roads) in your decision? If so, please list them here.]
Q3: Wie bist du bei deiner Entscheidung vorgegangen? Hattest du eine Strategie? Erkläre diese mit deinen eigenen Worten.
[How did you proceed in your decision making? Did you use any strategies? Please explain them in your own words.]
Q4: Wie schwierig hast du die Hauskaufaufgabe gefunden? 1 *steht für sehr einfach*, 5 *für sehr schwierig*.
[How difficult did you find the task of selecting a house to buy? 1 = *very easy*; 5 = *very difficult*.]
Q5: Wie hast du die verschiedenen Visualisierungen der Grenzen interpretiert? Was hat die Visualisierung deiner Meinung nach zu bedeuten?
[How did you interpret the different visualizations of the boundaries? What do you think these visualizations mean?]
Q6: Welche Darstellung der Grenze würdest du am ehesten mit Unsicherheit in Zusammenhang bringen?
[Which of the boundary visualizations would you consider most likely to represent uncertainty?]
Q7: Hast du jemals in deinem Leben ein Haus gekauft oder warst du bei einem Hauskauf näher involviert?
[Have you ever bought a house in your life or have you been involved in house buying decisions?]
Q8: Falls du die vorherige Frage mit Ja beantwortet hast, bitte ich dich zu erklären, wie du bei dem Hauskauf involviert warst und eventuell wie du bei deiner Entscheidung vorgegangen bist.
[If you responded "yes" to the previous question, please explain how you have been involved in the house purchase and maybe how you proceeded in arriving to your decision then.]
Q9: Hast du eine der dargestellen Ortscha-ften erkannt?
[Did you recognize any of the displayed locations?]
Q10: Falls du Frage 9 mit Ja beantwortet hast, bitte ich dich anzugeben, welche Dörfer du erkannt hast.
[If you responded "yes" to the previous question, please list the villages you did recognize.]